Universiteit
Leiden
Governance and Global Affairs

Comparative Analysis of GPTs and Open-Source LLMs for Annotating Parliamentary Discourse

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Motivation and Research Questions

Motivation and Disclaimer

Why incivility and policy agenda matters? Opportunities for MPs to question government ministers. Democratic accountability and dynamics between government and opposition.

Gladiatorial contest. The questioning could have a "combative" nature and garner media attention.

Proof-of-concept. ParlaMint data is *forthcoming*. This presentation's evidence is drawn from (own) prior studies on policy agenda and incivility benchmarks.

Artwork by DALL·E 3 model

Research Questions

Artwork by DALL·E 3 model

RQ1. How well do general-purpose LLMs' zero-shot capabilities transfer to political domains?

RQ2. What trade-off arises between proprietary GPTs (also reasoning models) and open-source models?

RQ3. How does task complexity (policy topics vs toxicity) influence those trade-offs?

Data and Tasks Already Benchmarked

Ground-Truth Policy Agenda

Denmark	NLD	UK	France
15 101 bills 1953–2016	4 684 bills 1981–2009	6 169 Acts 1911–2015	3 069 laws 1979–2013

Hungary	Italy	Brazil	Spain
8 220 bills 1990–2022	4 554 laws 1983–2013	2 449 laws 2003–2014	2 256 laws-decrees 1980–2018

Note. We split the samples in a proportion of 70/15/15 (stratified by major topic) for training, validation, and testing for future fine-tuning jobs. The samples correspond to ground-truth data of the Comparative Agendas Project.

Ground-Truth Toxicity

Arabic
5000 tweets manually annotated

Chinese
5000 messages for toxic detection

English
5000 Wikipedia comments

German
5000 Twitter and Facebook comments

Hindi
5000 Twitter and Facebook comments

Russian
5000 comments on social network OK

Spanish
5000 messages for toxic detection

Note. We split the samples in a proportion of 70/15/15 for training, validation, and testing in case of fine-tuning jobs. The samples correspond to ground-truth data prepared for CLEF TextDetox (2024).

LLMs Zero-Shot Classification

79/109 LLMs

Multiclass/Binary

Run **620/807 times** under different conditions (e.g., parameters, API/local, temperature, datasets/language)

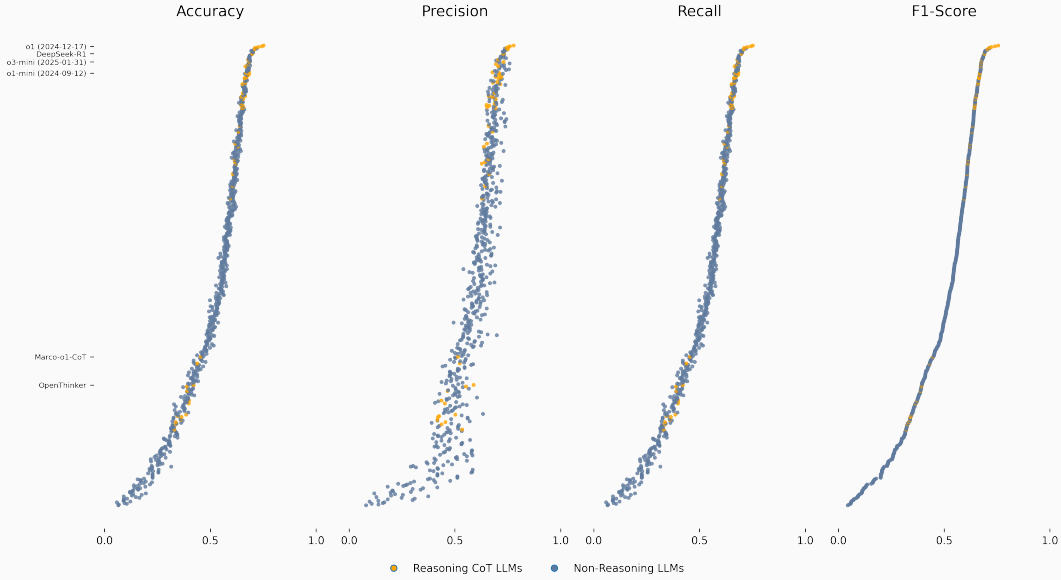
SOTA closed-source LLMs

o4-mini, o3-mini, o1, GPT-4.1, GPT-4.5-preview, Grok 3 Beta, Claude 4 Opus, among others

SOTA open-source LLMs

Llama 4 Maverick (400B) and Scout (107B), Mistral 3.1 (24B), Llama 3.3 (70B), DeepSeek-R1 (671B), DeepSeek-V3 (671B), among others

Benchmarking Policy Agenda


Accuracy
Precision
Recall
F1-Score
o1 (2024-12-17)
DeepSeek-R1
o3-mini (2025-01-31)
o1-mini (2024-09-12)
Marco-o1-CoT
OpenThinker
0.0
0.5
1.0
Reasoning CoT LLMs
Non-Reasoning LLMs

Top Performing Models Policy Agenda

0.76

Maximum F1-Score

Achieved by OpenAI reasoning models

0.69

Top Open-Source Models

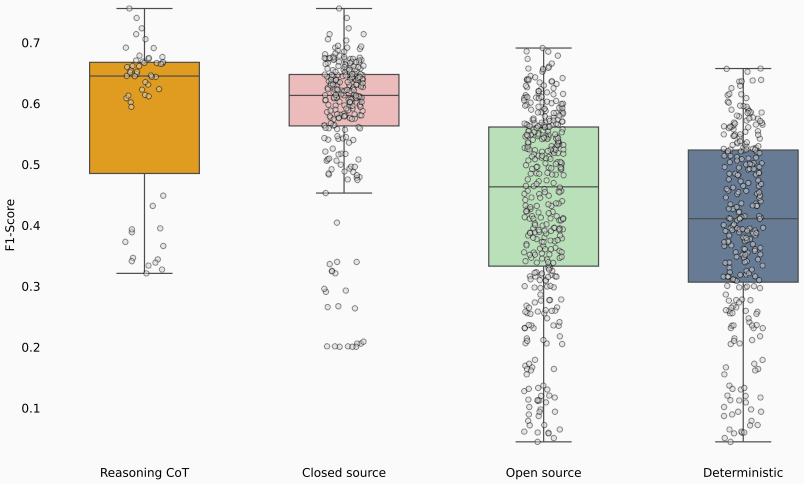
DeepSeek-R1 and V3 (926B) and Llama 3.1 (405B)

0.54

Mid-Range Performance

Gemini 1.5 series, GPT4o-mini, Mistral models, Qwen 2.5

F1-Score Across Reasoning, Source and Deterministic Setup



Comparing with Fine-Tuned Models

Language	Best LLM	F1-Score	Fine-Tuned	F1-Score	Δ Val	Δ Best LLM
Danish	GPT-4.5	0.679	Babel Machine	0.925	+0.065	+0.246
Dutch	o1	0.724	Babel Machine	0.906	+0.066	+0.182
English	o1	0.706	Babel Machine	0.869	−0.031	+0.163
			ft-XLM-RoBERTa	0.810	−0.009	+0.104
French	o1	0.714	Babel Machine	0.821	−0.029	+0.107
Hungarian	GPT.4-5	0.672	Babel Machine	0.751	−0.099	+0.079
Italian	o1	0.675	Babel Machine	0.930	+0.120	+0.255
Portuguese	o1	0.651	Babel Machine	0.867	−0.063	+0.216
Spanish	o4-mini	0.756	Babel Machine	0.916	+0.066	+0.160

Note. All estimates are weighted F1-scores obtained on our fixed held-out test set. The columns Δ Val and Δ Best LLM indicate: (i) the change relative to the best result on the model's own validation set; and (ii) the change relative to the strongest zero-shot LLM, respectively.

How much data leakage is present here? Probably considerable, so that the results may be inflated. However, the potential advantages of fine-tuning still seem to outweigh in-context learning, even for BERT-like models.

Key Findings Meta-Analysis Policy Agenda

$+8.9\%$

Reasoning Advantage

Chain-of-thought capabilities boost F1-score by almost 9 points

-7.8%

Reproducibility Penalty

Deterministic deployment reduces F1-score by about 8 points, but ensures consistency

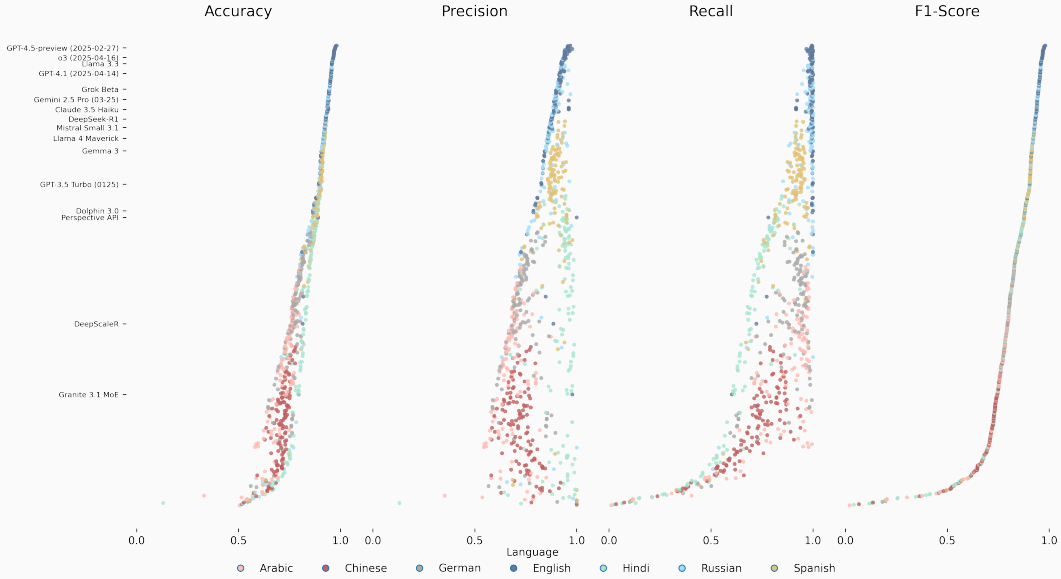
$\geq 10\%$

Fine-Tuning Advantage

Supervised transformers outperform zero-shot LLMs by 10+ points

We did not find 🔒 openness penalty

Benchmarking Toxicity


Accuracy
Precision
Recall
F1-Score
GPT-4.5-preview (2025-02-27)
o3 (2025-04-16)
Llama 3.3
GPT 4.1 (2025-04-14)
Grok Beta
Gemini 2.5 Pro (03-25)
Claude 3.5 Haiku
DeepSeek-R1
Mistral Small 3.1
Llama 4 Maverick
Gemma 3
GPT 3.5 Turbo (0125)
Dolphin 3.0
Perspective API
DeepScaleR
Granite 3.1 MoE
0.0
0.5
1.0
Language
Arabic
Chinese
German
English
Hindi
Russian
Spanish

Top Performing Models

Arabic

0.83 F1-Score

o3 · o1 · GPT-4.5

Chinese

0.78 F1-Score

GPT-4.1 · GPT-4o · Grok 3

English

0.98 F1-Score

Granite 3.2 · OLMo 2 · GPT-4.5

German

0.86 F1-Score

GPT-4.1 · o3 · GPT-4.5

Hindi

0.89 F1-Score

Mistral Saba · Mistral Medium 3 · Gemma 2

Russian

0.96 F1-Score

o3 · GPT-4.1 nano · Claude 4 Opus

Spanish

0.93 F1-Score

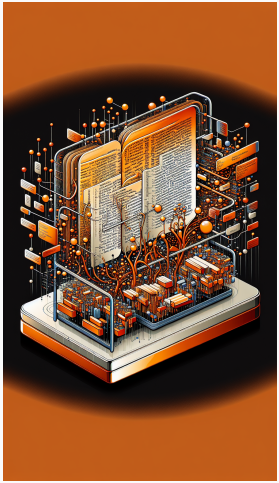
GPT-4.5 · o3 · GPT-4.1

Comparison to Perspective API

Perspective API performance. Competitive accuracy but abysmally low recall scores, resulting in low F1-scores across languages.

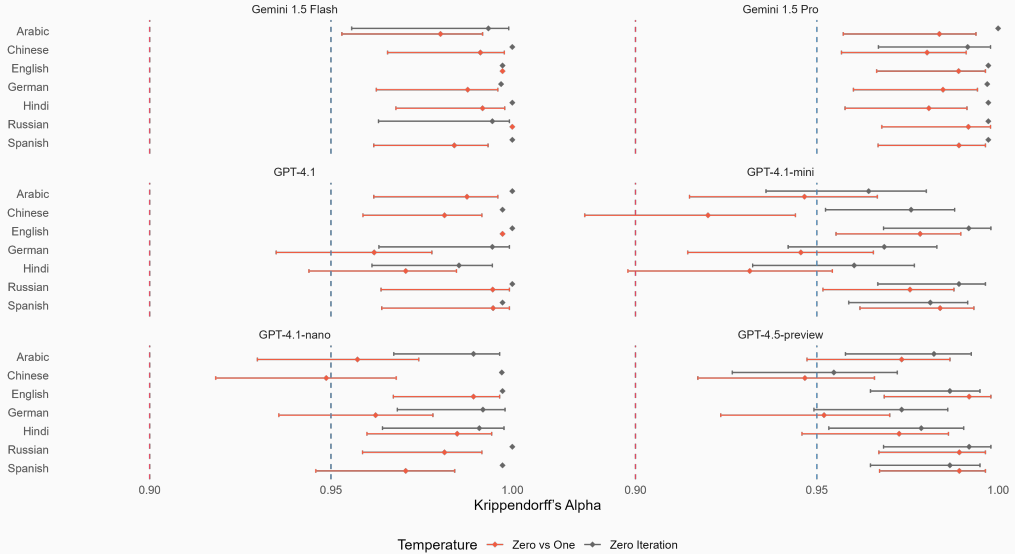
Performance gap. Even weakest LLMs outperform Perspective by about 0.20 points in F1-score for Arabic and Chinese.

Technological shift. Highlights transition from classical transformer pipelines to modern LLMs for toxicity classification.



Artwork by DALL·E 3 model

Temperature Experiments



Key Findings Meta-Analysis Toxicity

+7.7%

Resource Advantage

High-resource languages enjoy a 7.7 points F1 advantage

−9.8%

Size Penalty

Small models ($\leq$7B) fall 9.8 points short of larger LLMs baseline

99%

Annotation Reliability

Modern private LLMs exhibit outstanding reliability even w/temperature variations

We did not find 🔒 openness or 💡 overthinking penalties

Methodological Takeaways

Evidence-Based Recommendations

Reasoning advantage. Chain-of-thought capabilities enhance performance in policy agenda classification, but do not yield gains in toxicity classification.

Openness penalty inconclusive. Slight lower performance than proprietary models, descriptively. There is no significant effect in meta-analyses. However, deterministic deployment reduces F1-scores in policy agenda classification.

BERT family pays off in complex tasks. Supervised transformers outperform zero-shot LLMs by $+10$ points in policy classification. Even the weakest LLMs in toxicity outperformed off-the-shelf options.

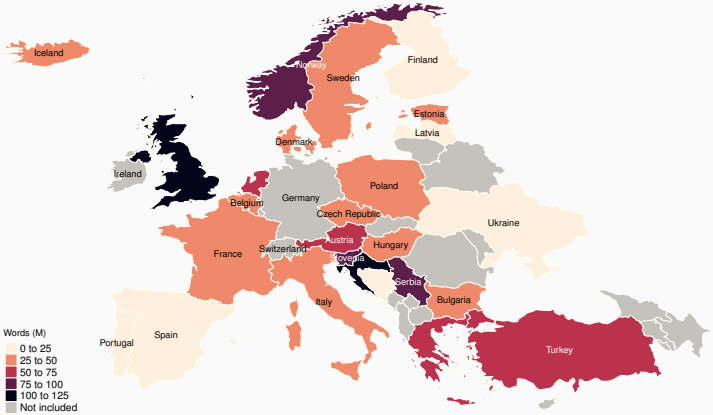
Performance vs reproducibility. Switching from deterministic to stochastic decoding rarely alters more than 1% of labels on average in toxicity.

Bridging to ParlaMint

Parliamentary Debates Data

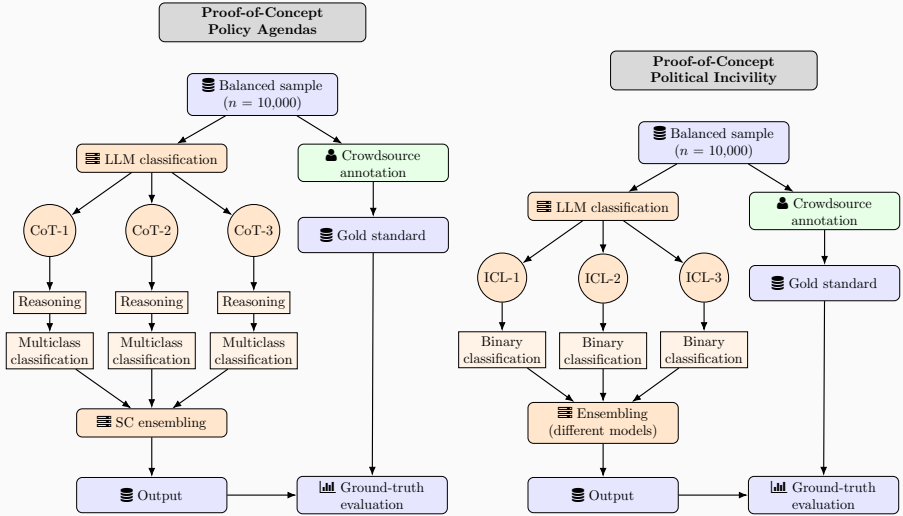
We shall use ParlaMint, which offers data on parliamentary debates of 26 European countries and three Spanish autonomous regions from about 2015 to mid-2022 (some countries even from the 1990s). The dataset offers not only the original speeches but also corpora linguistically annotated in the original languages and machine-translated versions of the texts.

ParlaMint Corpora ∼1.1B words



This implies that **∼7.5M utterances** were delivered in Parliament in the case of unicameral systems or some of the relevant chambers in bicameral systems.

Proof-of-Concept Pipeline



* We may replace reasoning LLMs with fine-tuned models.

Thank you very much!

Do you have any questions?

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Presentation compiled with LaTeX and some

Download the latest version from GitHub